TI 2010-102/3
Tinbergen Institute Discussion Paper

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Retirement choices in Italy: what an option value model tells us*

Michele Belloni † Rob Alessie ‡

Abstract

Using Italian data, we estimate an option value model to quantify the effect of financial incentives on retirement choices. As far as we know, this is the first empirical study to estimate the conditional multiple-years model put forward by Stock and Wise (1990). This implies that we account for dynamic self-selection bias. We also present an extended version of this model in which the marginal value of leisure is random.

The models yield plausible estimates of the preference parameters. Dynamic self-selection results in a considerable downward bias in the estimate of the marginal utility of leisure. We perform a simulation study to gauge the effects of a dramatic pension reform. Underestimation of the value of leisure translates into sizeable over-prediction of the impact of reform. For the female sample, the model is able to predict almost perfectly the age-specific hazard rates. For the male sample, we obtain a good fit. Results for males should, however, be interpreted with caution since we are not able to fully correct for dynamic self-selection bias.

Keywords: retirement, option value model, dynamic self-selection, unobserved preference heterogeneity

JEL codes: J26, H55, C33, C34, C35.

*The authors are grateful to Hugo Benitez-Silva, Axel Börsch-Supan, Christopher Flinn, Elsa Fornero, Eric French, Mike Hurd, Adriaan Kalwij, Steffen Reinhold, John Rust and Daniël van Vuuren for their useful comments. They also appreciate comments from participants at the ESPE 2010 conference, at the 7th workshop Marie Curie Research Training Network - The Economics of Ageing, at the workshop for the presentation of Ph.D. DSE thesis and at the seminars at MEA-Mannheim and the Central Planning Bureau. This research is partly supported by a grant from the Italian Ministry of Education, University and Research (MIUR). All opinions and errors are those of the authors alone.

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1 Introduction

Increasing the average retirement age is on the political agenda of almost all developed countries. It is generally accepted as the most effective solution to pay-as-you-go pension crises caused by population aging, increased life expectancy, and low growth. How to raise the retirement age is, however, subject to debate. Most policy measures focus on financial incentives, either by tightening access to benefits or by discouraging early retirement through, for example, the introduction of actuarially fair pension schemes. The effectiveness of these policies depends critically on the importance of financial incentives on retirement choices. The goal of this paper is to assess the impact of financial incentives on the retirement behavior of Italian employees.

The effects of financial incentives on retirement have been investigated in many studies, which use reduced-form models (see e.g. Gruber and Wise 2004b). It is well known (Lucas 1976) that structural models are more suitable than reduced-form models in evaluating the impact of reforms. Among the structural retirement models developed in the literature, the option value model (Stock and Wise 1990) is one of the best known. In this model, the worker is assumed to be forward looking. At each age, the worker chooses whether to retire by comparing the expected utility associated with retiring at the current age with the maximum among the expected utilities associated with retiring at any given future age. If the former is greater than the latter, then the worker retires; otherwise, the worker continues working. Transitions back to work are not modeled, since retirement is assumed to be an absorbing state.

In the option value (OV) model, individuals derive utility from both consumption and leisure. Consumption is approximated by current income. Leisure benefits only retirees (i.e., part-time work is excluded). Unobserved determinants of retirement - such as preference for leisure or health conditions - are accounted for in the stochastic component of the model. To allow for their persistency, Stock and Wise (1990) model the error term of the utility functions as an autoregressive process.

Dynamic programming (DP) (see e.g. Heyma 2004, Burkhauser, Butler, and Gumus 2004) is the best-known alternative approach to the OV model in the retirement literature. OV and DP models share some key features. They differ in the way uncertainty is treated: the OV model compares the expected utility associated with immediate retirement with the maximum of the expected utilities associated with future retirement, whereas DP models compare the expected value of the maximum of current and future retirement possibilities. Given Jensen's inequality, the OV model undervalues future options, thereby over-predicting retirement (Lumsdaine, Stock, and Wise 1995). However, various empirical applications show that OV and DP models yield similar results (see Lumsdaine, Stock, and Wise 1995, Burkhauser, Butler, and Gumus 2003).

Stock and Wise (1990) estimate two versions of the OV model: the single-year (SY henceforth) model and the multiple-years (MY) model. The SY model evaluates retirement probabilities in a single cross-section (base year). The MY model considers retirement decisions over time: If the worker does not retire in the base year, the worker re-evaluates the retirement decision in the following years on the basis of updated information on wages and pension benefits. In the MY model, one can allow for a more flexible stochastic specification of the OV model than the SY model, i.e., one can assess the extent of persistency of preference shocks.[1]

Stock and Wise (1990) select employees aged 50 and above when they estimate the SY model. Consequently, their cross-section (base year) data also contain old employees, e.g., aged 65. Note that such employees could have retired before the base year. Consequently, work-loving individuals might be over-represented in their estimation sample. In other words, estimates of the SY model may be inconsistent because of dynamic self-selection bias. In particular, by over-representing work-lovers, the SY model may underestimate the marginal utility of leisure. The estimates of the MY model presumably also suffer from dynamic self-selection bias, because older employees are also in the first wave of the longitudinal data set.

Stock and Wise (1990) were well aware of the dynamic self-selection problem. As a result, they formulated the *conditional* multiple-years OV model (CMY). The CMY model evaluates retirement probability in the base year and in subsequent years conditional upon retirement choices taken by workers prior to the base year. In this model, the likelihood contribution of older workers - who presumably began to consider retirement well before the base year - is a joint high-dimensional probability. The state-of-the-

[1] Stock and Wise (1990) assume that preference shocks are fully persistent when they estimate the SY model.

art in numerical integration existing at the time the Stock and Wise study was conducted did not permit a reliable approximation of high-dimensional integrals. This may explain why the authors did not estimate conditional probability models in their study.

Various papers on the OV model followed the seminal work of Stock and Wise. Although repeated observations for each individual were often available for the retirement analysis, almost all of these studies provide estimates for the SY version of the OV model.[2] Most of these studies find unsatisfactory results. For instance, Harris (2001) and Hurd, Loughran, and Panis (2003) make use of the Health and Retirement Study to test the OV model on a population of workers covered by heterogeneous pension schemes. These studies find implausible estimates for several critical coefficients, such as the marginal utility of leisure, and often a bad fit. Spataro (2000) performs a similar exercise on Italian survey data, finding comparable difficulties.

This paper contributes to the literature by providing an estimate of the CMY model, thereby accounting for dynamic self-selection. To our knowledge, no empirical applications of the conditional probability versions of the OV model exist in the literature. Little importance is placed on the effect of self-selection bias on the OV parameter estimates. We quantify this effect by also estimating SY and MY models and by comparing their estimated parameters with those of the CMY model.

Previous applications of the OV model account for heterogeneity in preferences due to observed characteristics. For instance, Stock and Wise (1990) allows for the marginal value of leisure to vary with worker age. However, van Soest, Kapteyn, and Zissimopoloulos (2007) argue that the preference for leisure is affected by factors not observed by the econometrician. To account for this, we estimate an extended version of the MY and CMY models, where the marginal value of leisure is random. These additional versions of the OV model may provide empirical evidence on the effect of dynamic self-selection bias on the (first and) second moments of the distribution of the marginal value of leisure: If not properly accounted for, a selected sample of work-loving individuals may lead to downward-biased estimates of population (mean and) variation of the marginal value of leisure.

In this exercise we use Italian administrative data. Information on earn-

[2]As far as we know, only Danø, Ejrnaes, and Husted (2005) exploits the longitudinal dimension of the data and estimates the MY model.

ings, social security benefits, and retirement choices are taken from the "Working History Italian Panel" (WHIP) data set merged with an additional pension file that provides information on seniority. This combined data set was previously used only by Belloni and Alessie (2009). In comparison with previous administrative data used to study retirement in Italy (see e.g. Brugiavini and Peracchi 2004), this data set has two main advantages. First, it allows for a more complete tracking of transitions into the labor market, providing a more precise definition of retirement status. Second, by reporting information on seniority, it permits an accurate reconstruction of worker financial incentives. Belloni and Alessie (2009) provide empirical evidence that, without good information on seniority, reduced-form models explaining retirement probability by means of financial incentives yield implausible results.

This paper proceeds as follows. Section 2 gives an overview of the Italian institutional framework. Sections 3 and 4 describe the OV model, the data, and sample selection. Section 5 summarizes the estimation results and presents a policy simulation. Section 6 sets forth our conclusions.

2 Institutions

Prior to the 1990s, the Italian social security system was characterized by a quite generous defined benefit (DB henceforth) formula and by attractive early retirement options. Benefits greater than 80 percent of the last wage were frequently granted. No actuarial adjustments were applied to early exits, generating a high "implicit tax" on continuing to work (Brugiavini 1999). This generosity was one of the main causes of the striking decrease in the labor force participation rate of older workers in Italy in the last decades of the twentieth century (see e.g. Brugiavini and Galasso 2004).

To re-establish the social security budget equilibrium, an impressive series of reforms were introduced by the Italian Government during the 1990s. The most notable reforms were those of 1992, 1995, and 1997. Continuous changes in the pension law, often fully applied after a long transitional phase, generated a complex legal framework. Moreover, different rules apply to different workers, although a partial harmonization has since been obtained. In this paper, we analyze the retirement behavior of employees enrolled in the *Fondo Pensioni Lavoratori Dipendenti* (FPLD) fund.[3] The FPLD is the main pension scheme for private sector employees. In 2008, it paid around 10 millions of benefits (INPS 2009). It is managed by the *Istituto Nazionale della Previdenza Sociale* (INPS), the most important social security institution in Italy.

The main exit routes to retirement for private sector employees have always been the old-age and seniority pensions. Prior to the 1992 reform, a female (male) employee could claim an old-age pension starting from age 55 (60), conditional on having accrued 15 years of seniority. Starting in 1993, the minimum eligibility age for the old-age pension was gradually raised to 60 (65) for females (males). Similarly, the minimum seniority rule was also tightened gradually by 5 years (from 15 years to 20 years). The transition to the new requirements for the old-age pension was then made shorter by a 1994 law.

Until 1995, the seniority pension could be claimed at any age, once 35 years of contributions had been accrued.[4] Consequently, employees who started their working careers rather early, could easily retire at roughly age 50.[5] The 1995 reform severely restricted access to the seniority pension in three ways. First, it gradually increased the minimum years of contribution from 35 to 40. Second, it introduced an alternative eligibility rule combining a minimum age with a minimum seniority.[6] Third, the reform introduced the 'exit window' mechanism, in which eligible workers who claim benefits must wait 3-12 additional months.[7] Furthermore, during the 1990s, access to seniority pensions was periodically blocked (e.g., in 1993), in order to avoid substantial exits resulting from an impulsive reaction of workers to the fear of further reforms.

The DB benefit formula is identical for both old-age and seniority pensions. It is computed as the product of three factors: pensionable earnings

[3]A comprehensive description of social security reforms in Italy is given in Brugiavini and Galasso (2004).

[4]According to our data, older female workers, whose careers are generally shorter and subject to more interruption than those of males, typically opt for an old-age pension. Older males, however, typically opt for a seniority pension.

[5]Note that, in addition to standard years of work, the valid contributory history of each individual also includes 'notional' contributions made during temporary out-of-work periods (e.g., unemployment, maternity leaves, and military service).

[6]The reform of 1997 made the transition to these rules quicker for white collar workers.

[7]Table 1 in Belloni and Alessie (2009) summarizes the reforms described above.

(PE), seniority, and return rate. PE is computed as the average earnings of the final years of work. The number of years to be counted in its computation was 5 before the reforms, and gradually raised to 10 by the reform of 1992. Given the generally upward-sloping lifetime wage profile, this legal change resulted mainly in lower pensions. It affected more white collar than blue collar workers, since the wage profile of the former is typically steeper than that of the latter. Up to 40 years of seniority can be accrued; working longer is thus discouraged (unless it increases PE). The return rate is a decreasing function of PE. However, a constant 2 percent return applies to most deciles of the earnings distribution. If the application of the above-described formula results in a benefit that is below a given threshold (so called *pensione minima*) and if an earnings test is passed, the difference is subsidized.

Payroll taxes for employees are particularly high. They grew from 25.21 to 32.7 percent of wages during the analyzed period. Two-thirds are paid by the employer and one-third by the employee. In principle, retirement is not compulsory to claim pension benefits. However, there is a strong financial incentive to retire at the time of claim; if a worker (particularly an employee) continues to work while collecting a pension, the workers total income is heavily taxed.[8] Our data confirm that very few pension beneficiaries work.

In addition to old-age and seniority pensions, other social security programs financing retirement in Italy include the disability pension and some types of unemployment benefits targeted to older workers (long-run mobility scheme, so-called *mobilità lunga*). Until the early 1980s, the disability pension was attractive, easily granted, and often used as an early retirement scheme. In 1984, a reform made its use less discretionary and subject to periodic medical checks. As a consequence of this reform, in a few years use of the disability pension as an early exit route was substantially reduced (Brugiavini 1999). Mobility programs temporarily subsidize workers who are collectively fired by firms during a recession, favoring re-employment in the labor market. The long-run mobility scheme has another aim, since it allows older workers who have few chances re-employment to retire prematurely. Therefore, it has been used as a 'bridge' to the old-age pension.[9]

[8] The legislation on this point is extremely complex and has been in continuous evolution for several last decades. Tax rules differ depending on the type of pension, type of worker, and year of application.

[9] Eligibility for the long-run mobility scheme requires a minimum age, seniority, and

3 The option value model

3.1 Analytical description

Suppose a forward-looking individual whose lifetime utility at time (year) t is given by $\sum_{s=t}^{\Omega} \beta^{s-t} u(c_s, l_s)$, where $u(.)$ is the instantaneous utility, c_s is consumption at time s, l_s is leisure, a dummy variable indicating whether or not an individual works. β denotes the discount factor and Ω the year in which the individual reaches the maximum attainable age. The model abstracts from saving, so that consumption is approximated by current income. The no-smoothing behavior may be a strong assumption, however, since it rules out the role of private wealth in financing retirement. Nevertheless, it is present in most of the literature on structural models of retirement behavior. There are a few relevant recent exceptions: French (2005), Blau (2008) and van der Klaauw and Wolpin (2008). In the Italian case, this assumption is plausible since the public social security system is extremely generous and is by far the main source of income during retirement (Brugiavini 1999).

Let Y_s be earnings from work in year s and $B_s(r)$ the pension and social security benefits received in year s if retirement is in year r ($s \geq r$). Then $u(Y_s, 0) = U_W(Y_s)$ in case the individual works and $u(B_s(r), 1) = U_R(B_s(r))$ in case the individual is retired.

The individual chooses in year t the retirement year r in such a way that the expected value of the following value function is maximized:

$$V_t(r) = \sum_{s=t}^{r-1} \beta^{s-t} U_W(Y_s) + \sum_{s=r}^{\Omega} \beta^{s-t} U_R(B_s(r)) \tag{1}$$

The individual solves this problem by comparing the expected value of retiring in year t with the greatest among the expected values of retiring in any future year r.[10] Define the expected gain from postponing retirement as

$$G_t(r^*) = E_t V_t(r^*) - E_t V_t(t) \tag{2}$$

where $r^* = \text{argmax } E_t V_t(r)$ for $r \in \{t+1, \ldots, t_{\max}\}$ and $t_{\max}$ is the year in which the worker reaches mandatory retirement age. The worker then retires in year t if $G_t(r^*) \leq 0$, otherwise the worker postpones retirement.

residency in areas characterized by high unemployment. Long-run mobility schemes were introduced in the early 1990s, and partly replaced the previous *pre-pensionamento*.

[10] According to the model, the employee faces three types of uncertainty: future income, lifetime and future preferences shocks (future values of ϕ_s and ψ_s in equations 6 and 7).

The instantaneous utilities have the constant relative risk aversion form

$$U_W(Y_s) = Y_s^\gamma + \upsilon_s \tag{3}$$
$$U_R(B_s) = (\kappa B_s(r))^\gamma + \omega_s \tag{4}$$

where the parameter κ represents the value of income in the status of retiree relative to income in the status of worker. We expect that individuals dislike work, i.e., $u(c_s, 1) > u(c_s, 0)$ or $\kappa > 1$. We specify κ as

$$\kappa = \kappa_0(\text{age}/50)^{\kappa_1} \tag{5}$$

This specification captures the possibility that the value of leisure rises with age due to, for example, increasing health problems ($\kappa_1 > 0$). The parameter γ represents the curvature of the utility function with respect to future income; it can also be interpreted as a measure of risk aversion. This parameter is expected to be less than one if workers are risk-averse and greater than one if they are risk-lovers. υ_s and ω_s are time-and-individual–specific random variables. υ_s and ω_s are assumed to be independent of earnings; they capture unobserved determinants of retirement, such as preference for leisure, private wealth, and health conditions. Since these determinants are typically persistent over time, the random variables are modeled as a first-order Markov process of the type[11]

$$\upsilon_s = \rho\upsilon_{s-1} + \phi_s \quad E_{s-1}(\phi_s) = 0 \tag{6}$$
$$\omega_s = \rho\omega_{s-1} + \psi_s \quad E_{s-1}(\psi_s) = 0 \tag{7}$$

Inserting equations (3-4) into equation (2) results in

$$\begin{aligned} G_t(r) = {} & E_t \sum_{s=t}^{r-1} \beta^{s-t}[Y_s^\gamma + \upsilon_s] + E_t \sum_{s=r}^{\Omega} \beta^{s-t}[(\kappa B_s(r))^\gamma + \omega_s] \\ & - E_t \sum_{s=t}^{\Omega} \beta^{s-t}[(\kappa B_s(t))^\gamma + \omega_s] \end{aligned} \tag{8}$$

Splitting it into a deterministic and a stochastic component, and accounting

[11] Like Stock and Wise (1990) we assume ρ to be the same in equations (6) and (7).

for survival probabilities yields

$$\begin{aligned} g_t(r) &= \sum_{s=t}^{r-1} \beta^{s-t}\pi(s|t)E_t[Y_s^\gamma] + \sum_{s=r}^{\Omega} \beta^{s-t}\pi(s|t)E_t[(\kappa B_s(r))^\gamma] \\ &\quad - \sum_{s=t}^{\Omega} \beta^{s-t}\pi(s|t)E_t[(\kappa B_s(t))^\gamma] \qquad (9) \\ \varphi_t(r) &= \sum_{s=t}^{r-1} \beta^{s-t}\pi(s|t)E_t[\upsilon_s - \omega_s] \qquad (10) \\ G_t(r) &= g_t(r) + \varphi_t(r) \qquad (11) \end{aligned}$$

where $\pi(s|t)$ are conditional survival probabilities.[12] Given the Markov assumption, $\varphi_t(r)$ simplifies to

$$\varphi_t(r) = \sum_{s=t}^{r-1} \beta^{s-t}\pi(s|t)\rho^{s-t}[\upsilon_t - \omega_t] \qquad (12)$$

Rewriting $K_t(r) = \sum_{s=t}^{r-1} (\beta\rho)^{s-t}\pi(s|t)$ and $\xi_t = \upsilon_t - \omega_t$, then

$$G_t(r) = g_t(r) + K_t(r)\xi_t \qquad (13)$$

Notice that the error term is heteroskedastic: the further the potential retirement age is in the future, the higher is $K_t(r)$. This model characteristic captures the greater uncertainty associated with future retirement.

3.2 Retirement probabilities

3.2.1 Single-year (SY) model

Suppose that we observe retirement choices in a single year (year t). The probability that a worker retires in t is given by

$$\Pr[R = t] = \Pr[G_t(r^*) \leq 0] = \Pr[g_t(r^*)/K_t(r^*) \leq -\xi_t] \qquad (14)$$

and $\Pr[R > t] = 1 - \Pr[R = t]$. Assuming that ξ_t is normally distributed with variance σ_ξ^2, the sample likelihood becomes

$$\mathscr{L} = \prod_i \Phi\left[-\frac{d_{it}g_{it}(r_{it}^*)}{K_{it}(r_{it}^*)\sigma_\xi}\right] \qquad (15)$$

[12] We implicitly assume that whether an individual is alive in future years is stochastically independent of the individuals stream of future earnings and of preference shocks.

where $d_{it} = 2y_{it} - 1$, and $y_{it} = 1$ if worker i retires in year t, while $y_{it} = 0$ otherwise. Φ is the standard normal c.d.f. The likelihood contains six unknown parameters: κ_0, κ_1,β, γ, σ_ξ and ρ. Standard maximum likelihood techniques can be applied to estimate them.

Estimation of the SY model requires only the availability of a single cross-section. Parameters are identified through between-individuals variation. However, in practice, a cross-section data set does not contain enough information to estimate ρ with great precision. Therefore, we follow Stock and Wise (1990) and assume that ξ_t follows a random walk process ($\rho = 1$). Another relevant shortcoming of the SY model concerns sample selection. For instance, a cross-section data set would typically include employees aged 60 who had the opportunity to retire before that age. These individuals might have chosen not to retire because they love working. The likelihood (15) does not take into account this type of endogenous sample selection. Consequently, maximizing the likelihood (15) would probably yield inconsistent estimates. In particular, the value of leisure may be underestimated, since individuals with a stronger preference for leisure may have exited the data before year t.

3.2.2 Multiple-years (MY) model

Suppose that we observe retirement choices for multiple years, say from t to T. Consider the case of a worker who retires in year τ, where $\tau \in \{t, ..., T\}$. Then, it must have been not optimal for that worker to retire up to year $\tau - 1$, i.e., that $G_t(r_t^*) > 0, ..., G_{\tau-1}(r_{\tau-1}^*) > 0$. In year τ, retirement is optimal, and therefore $G_\tau(r_\tau^*) \leq 0$. Specifying $G_t(r)$ as in equation (13), the (joint) probability for a worker to retire in year τ is given by

$$\begin{aligned}\Pr[R = \tau] \quad = \quad & \Pr[g_t(r_t^*)/K_t(r_t^*) > -\xi_t, ..., \\ & g_{\tau-1}(r_{\tau-1}^*)/K_{\tau-1}(r_{\tau-1}^*) > -\xi_{\tau-1}, \\ & g_\tau(r_\tau^*)/K_\tau(r_\tau^*) \leq -\xi_\tau]\end{aligned} \tag{16}$$

For reasons explained in the data section, we do not observe all workers retiring in the sample period. Therefore, the probability that the individual does not retire by year T is given by

$$\begin{aligned} \Pr[R > T] &= \Pr[g_t(r_t^*)/K_t(r_t^*) > -\xi_t, ..., \\ &\quad g_{T-1}(r_{T-1}^*)/K_{T-1}(r_{T-1}^*) > -\xi_{T-1}, \\ &\quad g_T(r_T^*)/K_T(r_T^*) > -\xi_T] \end{aligned} \tag{17}$$

The following Markov process is assumed for ξ_s[13]

$$\xi_s = \rho\xi_{s-1} + \nu_s \quad \nu_s \sim \text{NID}(0, \sigma_\nu^2) \tag{18}$$

for $s = t+1, ..., \tau$, while $\xi_t \sim \text{NID}(0, \sigma_\xi^2)$. It follows that the vector $\xi_t, \ldots, \xi_\tau$ is multivariate normal distributed with mean zero, $\text{var}(\xi_s) = \rho^{2(s-t)}\sigma_\xi^2 + \sum_{i=0}^{s-t-1} \rho^{2i}\sigma_\nu^2$ and $\text{cov}(\xi_s, \xi_t) = \rho^{s-t}\text{var}(\xi_t)$.

The individual i-th contribution to the sample likelihood is therefore

$$\mathscr{L}_i = \int_{-\infty}^{A_{i\tau}} \cdots \int_{-\infty}^{A_{it}} f\left(\xi_t, \ldots, \xi_\tau\right) \mathrm{d}\xi_t \ldots \mathrm{d}\xi_\tau \tag{19}$$

where $A_{i\tau}$ and A_{it} are the $(\tau - t + 1)$-th and the first element, respectively, of the vector

$$\begin{aligned} A_i &= \{g_{it}(r_{it}^*)/[K_{it}(r_{it}^*)\sigma_\xi], \ldots, \\ &\quad g_{i\tau-1}(r_{i\tau-1}^*)/[K_{i\tau-1}(r_{i\tau-1}^*)\sqrt{\text{var}(\xi_{\tau-1})}], \\ &\quad -[d_{i\tau}g_{i\tau}(r_{i\tau}^*)]/[K_{i\tau}(r_{i\tau}^*)\sqrt{\text{var}(\xi_\tau)}]\} \end{aligned}$$

and $d_{i\tau} = 2y_{i\tau} - 1$, and $y_{i\tau} = 1$ if worker i retires in year $\tau \in \{t, \ldots, T\}$ while $y_{i\tau} = 0$ otherwise. f is the multivariate standard normal density. The MY model is thus a kind of multivariate probit model with dependent errors.

Seven parameters must be estimated: κ_0, κ_1, β, γ, σ_ξ, σ_ν and ρ. We apply simulated maximum likelihood methods to estimate them. Given its desirable properties (Hajivassiliou, McFadden, and Ruud 1996, Hajivassiliou 2000), we use the GHK simulator to approximate the multi-dimensional integral present in the likelihood (19).

[13] Instead of the AR(1) process, we also experimented with the following specification for ξ put forward by Danø, Ejrnaes, and Husted (2005): $\xi_s = \mu + \epsilon_s$ where $\mu \sim NID(0, \sigma_\mu^2)$ and $\epsilon_s \sim NID(0, \sigma_\epsilon^2)$. The attractive feature of this model is that by conditioning on the individual effect μ, the likelihood function is reduced to a one-dimensional integral and thus is much easier to compute. However, it turned out that by using this specification for ξ, the fit of the model becomes much worse.

The longitudinal dimension of the data set allows precise estimation of the correlation coefficient ρ. Time variability can also be helpful in identification of other model parameters. This is especially true if, in the period under analysis, policy changes affected workers' financial incentives. This is the case in our sample (see section 2).

Like Stock and Wise (1990), we impose an age selection on the data. Consequently, the first wave of our longitudinal estimation sample contains old employees, e.g., aged 65. Note that such employees could have retired earlier. Consequently, work-loving individuals might be over-represented in our estimation sample. Therefore, as in the SY model, the MY model may provide inconsistent estimates - especially for the κ parameters - due to sample selection bias.

3.2.3 Conditional multiple-years (CMY) model

Stock and Wise (1990) have proposed a method to correct for the sample selection bias problem described above. Assume that workers begin considering retirement in year $t_0 \leq t$. According to the CMY model, the probability that a worker retires in year τ, for $\tau \in \{t, ..., T\}$, is

$$\begin{aligned}
\Pr[R = \tau | R > t-1] &= \Pr[R = \tau] / \Pr[R > t-1] = \\
&\Pr[g_{t_0}(r^*_{t_0})/K_{t_0}(r^*_{t_0}) > -\xi_{t_0}, \ldots, \\
&g_{\tau-1}(r^*_{\tau-1})/K_{\tau-1}(r^*_{\tau-1}) > -\xi_{\tau-1}, \\
&g_{\tau}(r^*_{\tau})/K_{\tau}(r^*_{\tau}) \leq -\xi_{\tau}] / \\
&\Pr[g_{t_0}(r^*_{t_0})/K_{t_0}(r^*_{t_0}) > -\xi_{t_0}, \ldots, \\
&g_{t-1}(r^*_{t-1})/K_{t-1}(r^*_{t-1}) > -\xi_{t-1}]
\end{aligned} \tag{20}$$

and

$$\begin{aligned}
\Pr[R > T | R > t-1] &= \Pr[R > T] / \Pr[R > t-1] = \\
&\Pr[g_{t_0}(r^*_{t_0})/K_{t_0}(r^*_{t_0}) > -\xi_{t_0}, \ldots, \\
&g_{T}(r^*_{T})/K_{T}(r^*_{T}) > -\xi_{T}] / \\
&\Pr[g_{t_0}(r^*_{t_0})/K_{t_0}(r^*_{t_0}) > -\xi_{t_0}, \ldots, \\
&g_{t-1}(r^*_{t-1})/K_{t-1}(r^*_{t-1}) > -\xi_{t-1}]
\end{aligned} \tag{21}$$

. The individual i-th contribution to the sample likelihood is

$$\mathscr{L}_i = \frac{\int_{-\infty}^{B_{i\tau}} \cdots \int_{-\infty}^{B_{it_0}} f(\xi_{t_0}, \ldots, \xi_{\tau})\, \mathrm{d}\xi_{t_0} \ldots \mathrm{d}\xi_{\tau}}{\int_{-\infty}^{C_{it-1}} \cdots \int_{-\infty}^{C_{it_0}} f(\xi_{t_0}, \ldots, \xi_{t-1})\, \mathrm{d}\xi_{t_0} \ldots \mathrm{d}\xi_{t-1}} \tag{22}$$

where $B_{i\tau}$ and B_{it_0} are the $(\tau - t_0 + 1)$-th and the first element, respectively, of the vector

$$\begin{aligned} B_i &= \{g_{it_0}(r^*_{it_0})/[K_{it_0}(r^*_{it_0})\sigma_\xi], \ldots, \\ &\quad g_{i\tau-1}(r^*_{i\tau-1})/[K_{i\tau-1}(r^*_{i\tau-1})\sqrt{\text{var}(\xi_{\tau-1})}], \\ &\quad -[d_{i\tau}g_{i\tau}(r^*_{i\tau})]/[K_{i\tau}(r^*_{i\tau})\sqrt{\text{var}(\xi_\tau)}]\} \end{aligned} \tag{23}$$

while C_{it-1} and C_{it_0} are the $(t - t_0)$-th and the first element, respectively, of the vector

$$\begin{aligned} C_i &= \{g_{it_0}(r^*_{it_0})/[K_{it_0}(r^*_{it_0})\sigma_\xi], \ldots, \\ &\quad g_{it-1}(r^*_{it-1})/[K_{it-1}(r^*_{it-1})\sqrt{\text{var}(\xi_{t-1})}]\} \end{aligned}$$

and f is the multivariate standard normal density.

The unknown parameters and the optimization methods used to estimate the CMY model are the same as the MY model. In addition, one needs a) an assumption on the first age at which workers begin to evaluate retirement, and b) a sufficiently long data set to permit observation of retirement choices from that age onwards, for each worker in the sample in year t. For instance, if the first age at which workers begin to evaluate retirement is set at 50, a worker aged 65 in t needs to be observed retrospectively starting from year $t_0 = t - 15$. In principle, retirement may even occur in the first year of employment. In practice, one may assume that the first possible retirement age is the first age at which exits to retirement are observed in the data, e.g., age 50.

3.2.4 Random preferences for leisure (RL models)

Up to now, we have discussed a retirement choice model that allows for heterogeneity in preferences due to age (see equation 5). However, van Soest, Kapteyn, and Zissimopoloulos (2007) argue that the marginal value of leisure is affected by factors not observed by the econometrician. Therefore we consider the following, more general specification of the κ parameter:

$$\kappa = (\kappa_0 + \zeta)(\text{age}/50)^{\kappa_1} \tag{24}$$

where the time invariant random preference term ζ is assumed to be normally distributed, i.e., $\zeta \sim NID(0, \sigma^2_\zeta)$. We also assume that ζ is stochastically independent of ξ_t and $\nu_s, s = t + 1, \ldots, \tau$ (cf. equation 18) and of the other right-hand side variables of the model. Due to these model extensions, the likelihood functions of the MY and CMY models become slightly more complex because one must address the unknown random preference term ζ. In the case of the MY model, the likelihood contribution of individual i (cf. equation 19) becomes (MY-RL)

$$\mathscr{L}_i = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{A_{i\tau}} \cdots \int_{-\infty}^{A_{it}} f\left(\xi_t, \ldots, \xi_\tau\right) \mathrm{d}\xi_t \ldots \mathrm{d}\xi_\tau \right] \frac{1}{\sigma_\zeta} \phi\left(\frac{\zeta}{\sigma_\zeta}\right) \mathrm{d}\zeta \tag{25}$$

The likelihood contribution of the CMY model (cf. equation 22) is adjusted in a similar fashion (CMY-RL):

$$\mathscr{L}_i = \frac{\int_{-\infty}^{\infty} \left[\int_{-\infty}^{B_{i\tau}} \cdots \int_{-\infty}^{B_{it_0}} f\left(\xi_{t_0}, \ldots, \xi_\tau\right) \mathrm{d}\xi_{t_0} \ldots \mathrm{d}\xi_\tau \right] \frac{1}{\sigma_\zeta} \phi\left(\frac{\zeta}{\sigma_\zeta}\right) \mathrm{d}\zeta}{\int_{-\infty}^{\infty} \left[\int_{-\infty}^{C_{it-1}} \cdots \int_{-\infty}^{C_{it_0}} f\left(\xi_{t_0}, \ldots, \xi_{t-1}\right) \mathrm{d}\xi_{t_0} \ldots \mathrm{d}\xi_{t-1} \right] \frac{1}{\sigma_\zeta} \phi\left(\frac{\zeta}{\sigma_\zeta}\right) \mathrm{d}\zeta} \tag{26}$$

Since we assume that ζ is normally distributed, we can use the Gauss-Hermite quadrature to integrate out the unknown random preference term ζ, which speeds the estimation process considerably. However, there is a disadvantage associated with the normality assumption, because it implies a positive probability that κ is smaller than zero. From an economic viewpoint, a negative κ is highly implausible, because in that case the marginal utility of consumption would be negative for retirees. It should be stressed, however, that the empirical results (see below) suggest an extremely small probability of a negative κ.

3.3 Computation of $g_t(r)$

In order to compute $g_t(r)$ (see equation 9), we need to evaluate, for each worker in the sample, the following expectations: $E_t\left[Y_s^\gamma\right]$ and $E_t[(\kappa B_s(r))^\gamma]$ for $s > t$. Consider the wage model in Belloni and Alessie (2009). This model can be rewritten as follows[14]

$$\begin{aligned} \ln(Y_{it}) &= \theta_{t-yob_i} + \lambda_t + c_i + u_{it} && (27) \\ u_{it} &= \varrho u_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim NID(0, \sigma_\epsilon^2) && (28) \end{aligned}$$

where Y_{it} denotes real annualized wages net of social security contributions paid by the employer , yob_i denotes year of birth and c_i is a random effect

[14]Cf. equations (4) and (5) in Belloni and Alessie (2009).

capturing individual unobserved heterogeneity. The θ-parameters capture age effects, and the λ-parameters time effects. In equation (27), the θ and λ-parameters cannot be identified separately due to the perfect collinearity between the variables age (i.e., $t - yob_i$), calendar year and year of birth (subsumed in c_i). To address this problem, we follow the suggestion of Deaton and Paxson (1994), and impose the following two restrictions on the λ-parameters: 1) they add up to zero; and 2) they are orthogonal to a time trend. The wage model (27)-(28) is estimated separately by gender and occupation (blue versus white collar workers) using WHIP data.[15]

Equations (27) and (28) imply that for $s > t$

$$\begin{aligned} E_t\left(Y_{is}^{\gamma}\right) &= Y_{it}^{\gamma} E_t \exp(\gamma(\ln Y_{is} - \ln Y_{it})) \\ &= Y_{it}^{\gamma} \exp(\gamma((\theta_{s-yob_i} - \theta_{t-yob_i}) + (\varrho^{s-t} - 1)u_{it}) E_t\left(\exp(z_{it}^s)\right) \end{aligned}$$

where $z_{it}^s = \gamma \sum\limits_{j=t+1}^{s} \varrho^{s-j}\epsilon_{ij}$. Since the income shocks ϵ_{ij} are assumed to be normally distributed (cf. equation 28), it holds that $z_{it}^s \sim N(0, \sigma_{ts}^2)$, where

$$\sigma_{ts}^2 = \sigma_\epsilon^2 \gamma^2 \sum_{j=t+1}^{s} \varrho^{2(s-j)} = \sigma_\epsilon^2 \gamma^2 \frac{1 - (\varrho^2)^{s-t}}{1 - \varrho^2}$$

Consequently,

$$E_t\left(Y_{is}^{\gamma}\right) = Y_{it}^{\gamma} \exp(\gamma((\theta_{s-yob_i} - \theta_{t-yob_i}) + (\varrho^{s-t} - 1)u_{it})) \exp(\sigma_{ts}^2/2) \quad (29)$$

Following Stock and Wise (1990),[16] we approximate $E_t[(\kappa B_s(r))^{\gamma}]$ with $(\kappa_0(\text{age}/50)^{\kappa_1} \bar{B}_s(r))^{\gamma}$. $\bar{B}$ is the social security benefit, computed on the basis of observed wages up to year t and of forecasted wages from year $t+1$ to year $r-1$. Forecasts are based on the wage model (27)-(28).

We consider pension rules only for old-age and seniority pensions in the FPLD scheme.[17] We assume that workers know current pension rules and hold static expectations, i.e., that they make their retirement plans assuming that the current rules will not be changed by future reforms. This is a rather

[15] The estimation results are shown in Belloni and Alessie (2009). We also experiment with alternative assumptions on the wage process, such as an autoregressive model and a model with constant expected wages. OV parameter estimates turn out to be robust to the different wage profiles.

[16] See footnote 12 in Stock and Wise (1990).

[17] See Belloni and Alessie (2009) appendix A.1. for a formal description of the DB formulas.

standard assumption in the retirement literature (see e.g., Gruber and Wise (2004b) and Brugiavini and Peracchi (2004) for Italy). We realize that such an assumption may be strong in the period of the reforms. Nevertheless, properly accounting for alternative expectation formation schemes would require subjective data on expected future pension rights (see e.g. Bottazzi, Jappelli, and Padula 2006, Chan and Stevens 2004).

Survival probabilities in $g_t(r)$ are evaluated allowing for variation by age, gender, cohort, and region. The Italian Institute of Statistics publishes a long time series of life tables by age, gender, and region (ISTAT 2008). From these data, we disentangle age from year of birth effects on mortality rates. As in Brugiavini and Peracchi (2003) and Belloni and Alessie (2009), we apply a minimum-χ^2 method for the log-odds of mortality, using age and cohort as explanatory variables. The model is estimated separately by gender and region, for a total of 36 estimated models. Fitted values from these models are then used to predict survival probabilities.

4 Data and sample selection

4.1 The WHIP data

We use the WHIP data linked with an additional INPS pension file. WHIP is a random sample of the private sector non-agricultural workforce. It is drawn from an administrative archive managed by INPS. Workers are followed insofar as they pay social security contributions to INPS or receive social security (e.g., unemployment or pension) benefits. Workers leave the archive when they stop contributing (e.g., because they leave the labor force, or start working in the public sector), or when they die. Therefore, the panel is unbalanced.

WHIP comprises a principal file - the 'O1M data' file - and other complementary files. The O1M data report main employment spells characteristics such as wages, occupation, weeks worked and contract type. They cover the period 1985-2001. The complementary files focus on spells of self-employment (artisans and traders), unemployment and mobility. They mainly show related earnings (or benefits). Information on pension benefits is obtained from an additional INPS pension file.[18] This additional file shows

[18]Seniority cannot be observed for every worker in the WHIP data, but only for those who received pension benefits in the years 1985-2006. As a consequence, we cannot deter-

the pension amount, the date of first payment, and the accrued seniority at retirement of all pensions paid by INPS during the period 1985-2006.

These data were previously used only by Belloni and Alessie (2009). Other recent studies on retirement in Italy instead use the O1M data (see, e.g. Brugiavini and Peracchi 2004). In comparison with the O1M data, our data have two main advantages. The most important is that they report seniority. Belloni and Alessie (2009) provide empirical evidence that, without good information on seniority, reduced-form models explaining retirement probability by means of financial incentives give implausible results. Obviously, information on seniority is also extremely relevant to our study. Second, our data better track transitions into the labor market. Previous studies assume that workers were retired when they permanently left the O1M data. This assumption may be strong if employees transit to retirement non-smoothly, e.g., passing though periods of self-employment. Thanks to the complementary files, we may relax this assumption.

The main weakness of WHIP is that transitions from and to the public sector cannot be observed. In our study this is not important, however, since we focus on workers aged 50 and older. Transitions between private and public sector are rare for these workers.[19] Another weakness of our data is that few individual characteristics (gender, date and region of birth) can be observed. Finally, family status and household characteristics are not available.

4.2 Sample selection

Sample selection is illustrated in figures 1 and 2 for females and males, respectively. We select females aged 50 to 60 born between 1935 and 1945. Empirical evidence shows that only a negligible number of female employees retire before age 50 and after age 60. In the SY model, we examine their retirement choices in 1995 (grey area in figure 1). Note that by choosing this base year, we know seniority for everyone in the sample.[20] This allows

mine seniority for some groups of workers, including: 1) young workers who retire after 2006; and 2) older workers who worked partly in the private sector - but not enough to become eligible for INPS benefits - and partly in the public (or agricultural) sector.

[19]See Richiardi, Pierro, Sella, Borella, and Moscarola (2009), who use EU-SILC data to simulate transitions in the Italian labor market.

[20]Suppose that we had chosen 2000 as the base year. The selected cohorts would have been 1940-1950. Especially for the 1950 cohort, seniority would not have been observed

Figure 1: Sample selection: females

cohort	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
1935	50	51	52	53	54	55	56	57	58	59	**60**						
1936		50	51	52	53	54	55	56	57	58	**59**	60					
1937			50	51	52	53	54	55	56	57	**58**	59	60				
1938				50	51	52	53	54	55	56	**57**	58	59	60			
1939					50	51	52	53	54	55	**56**	57	58	59	60		
1940						50	51	52	53	54	**55**	56	57	58	59	60	
1941							50	51	52	53	**54**	55	56	57	58	59	60
1942								50	51	52	**53**	54	55	56	57	58	59
1943									50	51	**52**	53	54	55	56	57	58
1944										50	**51**	52	53	54	55	56	57
1945											**50**	51	52	53	54	55	56

Notes: numbers in the figure represent ages at retirement risk; the SY model is estimated in the grey area; the MY model is estimated in the solid-line framed area; the CMY model is estimated in the solid-line framed area and exploits information in the dashed-line framed area.

us to compute pension rights in the correct way (see section 2). In the MY (and MY-RL) model, we follow the selected group of females from 1995 onward until retirement or up to 2001 (solid-line framed area in figure 1). In the CMY (and CMY-RL) model for the individuals in the sample in 1995 (to correct for sample selection bias, see equation (22)) we also use the information available in the period 1985-1994 insofar as the worker is aged at least 50 (dashed-line framed area in figure 1).[21]

A preliminary data analysis suggests that males do not retire before age 50. Contrary to females, some males continue to work after age 60. However, almost all retire before age 66. Therefore, we consider retirement choices between 50 and 65. Since 2006 is the last year for which seniority is available, the youngest cohort that we consider in the sample is 1941 (i.e., 2006-65). This implies that the most appropriate choice for the base year is 1991 (i.e., 2006-(65-50)). In other words, for the estimation of the SY model, we select males born between 1926 and 1941 who are not retired at the beginning of 1991 (grey area in figure 2). In the MY (and MY-RL)

for everyone, since some individuals were not retired before 2006 (the last year covered by the pension file). In the sample preparation, we should delete those individuals for whom seniority is not known. Therefore this choice of base year would have resulted in selecting only individuals with a taste for leisure.

[21] Note that choosing as the base year one of the years between 1985 and 1994 instead of 1995 results in a partial correction for self-selection bias in the CMY models. Choosing as the base year one of the years between 1997 and 2001 results in the self-selection problem described in footnote 20.

Figure 2: Sample selection: males

cohort	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
1926	59	60	61	62	63	64	65										
1927	58	59	60	61	62	63	64	65									
1928	57	58	59	60	61	62	63	64	65								
1929	56	57	58	59	60	61	62	63	64	65							
1930	55	56	57	58	59	60	61	62	63	64	65						
1931	54	55	56	57	58	59	60	61	62	63	64	65					
1932	53	54	55	56	57	58	59	60	61	62	63	64	65				
1933	52	53	54	55	56	57	58	59	60	61	62	63	64	65			
1934	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65		
1935	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	
1936		50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65
1937			50	51	52	53	54	55	56	57	58	59	60	61	62	63	64
1938				50	51	52	53	54	55	56	57	58	59	60	61	62	63
1939					50	51	52	53	54	55	56	57	58	59	60	61	62
1940						50	51	52	53	54	55	56	57	58	59	60	61
1941							50	51	52	53	54	55	56	57	58	59	60

Notes: see figure 1.

model, we follow these individuals from 1991 onward until retirement or up to 2001 (solid-line framed area in figure 2). In the CMY (and CMY-RL) model for individuals in the sample in 1991, we use the information available in the period 1985-1991 insofar as the worker is aged at least 50 (dashed-line framed area in figure 2). The correction for self-selection is incomplete for males, since workers born in 1934 or earlier can be observed only after age 50. For instance, the 1926 generation can be followed starting from age 59 onward (i.e., 1985-1926).

As already discussed, we focus on retirement choices of private sector employees enrolled in the FPLD fund. An employee is considered retired if he/she leaves permanently the O1M archive and is not later self-employed (either as an artisan or a trader). Given that we evaluate voluntary retirement choices, we do not consider transitions out of the labor force due to disability and mobility subsidies.[22]

5 Results

Tables 1 and 2 show results for females and males, respectively. They report the estimated parameters for five variants of the OV model: SY, MY and

[22] Our data reveal that transitions to retirement through disability are rare (see also Brugiavini 1999). Transitions through mobility schemes represent about 6 percent of all transitions into retirement.

CMY, plus the random coefficient versions of the MY and CMY models (MY-RL and CMY-RL). As discussed in subsection 3.1, we follow Stock and Wise (1990) and parameterize κ as a function of age (cf. equation 24). It turns out that for females, the estimate of the age parameter κ_1 does not differ significantly from zero for all models. Therefore we set $\kappa_1 = 0$ for females.

We set the value of the discount factor β to 0.76. This estimate was obtained in Stock and Wise (1990). According to these authors, this value of β is rather plausible. They justify this claim as follows: "Although a narrow interpretation of the parameters of the model would treat β as a general measure of individuals' pure rate of time preference, independent from the decision to which it applies, it is probably more realistic to think of it as a weight specific to the retirement decision." Without fixing the value of this parameter, we obtain implausibly low estimates for β.[23] Other relevant studies (see e.g. Danø, Ejrnaes, and Husted 2005, Burkhauser, Butler, and Gumus 2003) also fix the value for the discount factor.

5.1 Females

As explained in section 4, the SY model is estimated on the 1995 wave of the WHIP data, where we select workers aged 50-60. Moreover, following the literature, we assume that $\rho = 1$. The estimate of κ ($\kappa_0 = 0.94$) suggests that female employees are work-lovers. However, this estimate does not differ significantly from 1. In subsection 3.2.1, it is explained that the SY model may provide an estimate for κ that is biased downwards due to self-selection.

In the MY model, we take the same sample of workers considered in the SY model, but those who do not retire in 1995 are followed for more years until they retire or up to 2001. Note that Stock and Wise (1990) use only 3 years, while we use 7 years. Eight outcomes are possible in our sample: retire in one of the years between 1995 and 2001, or do not retire. The period 1995-2001 includes various changes in the pension rules, which affected worker retirement incentives in this period. Due to these pension reforms, the preference parameters are presumably estimated with higher precision.

According to the MY model the estimate of ρ is equal to 0.43 (s.e. 0.06).

[23]We also estimate the models by setting $\beta = 0.90$. Although in this case the fit deteriorates somewhat, the estimation results are qualitatively similar.

Table 1: Option value parameter estimates: females

	Model				
	SY	MY	CMY	MY-RL	CMY-RL
Parameter					
κ_0	0.938	1.758	2.087	2.554	3.241
	(0.055)	(0.089)	(0.117)	(0.162)	(0.246)
γ	0.252	0.317	0.281	0.339	0.326
	(0.068)	(0.051)	(0.052)	(0.064)	(0.069)
ρ	1*	0.426	0.581	0.661*	0.661
	-	(0.058)	(0.041)	-	(0.038)
σ_ξ	1.057	8.859	5.037	6.067	5.889
	(0.221)	(3.078)	(1.929)	(2.443)	(2.944)
σ_ν		4.632	3.230	2.471	3.147
		(1.679)	(1.139)	(1.003)	(1.492)
σ_ζ				1.321	1.819
				(0.136)	(0.204)
Summary statistics					
N.Obs.	1341	5341	5341/9079	5341	5341/9079
N.Ind.	1341	1341	1341	1341	1341
-log $\mathscr{L}$	409.28	1667.14	1653.16	1630.74	1588.32
est.method	ML	SML	SML	SML,GHQ	SML,GHQ

Notes: $\beta = 0.76$; $\kappa_1 = 0$; * = value imposed; s.e. in parenthesis; monetary values are in €1,000 (2009 euros); ML is maximum likelihood, SML is simulated maximum likelihood (GHK simulator with 100 random draws plus antithetics), GHQ is Gauss-Hermite quadrature (10 points).

Apparently, preference shocks are much less persistent than assumed in the SY model (where $\rho = 1$). At the same time, the MY estimate for κ ($\kappa_0 = 1.76$) is much larger than the corresponding SY estimate (0.94). Moreover, from an economic viewpoint, the MY estimate of κ is more plausible (i.e., significantly greater than 1).

The MY model is also estimated by Stock and Wise (1990) for males. As they point out themselves, their estimates may be inconsistent due to the dynamic self-selection problem. We claim that, for this reason, the estimate for κ might be biased downwards. Stock and Wise (1990) suggest a conditional probability model to correct for self-selection (see section 3.2.3 of this paper). However, these authors do not estimate this model. To our knowledge, ours is the first empirical study that explicitly accounts for dynamic self-selection in the context of the OV model.

According to the CMY model, κ_0 is found to be 2.09. This parameter is very precisely estimated. The value of leisure is high for females: they evaluate €1 of income during retirement as more than double €1 of income while working. In other words, female workers are available to retire provided that they are given a replacement rate equal to at least 49 percent. The CMY estimate of κ_0 is somewhat larger that the corresponding MY estimate (2.09 versus 1.76). This comparison suggests that dynamic self-selection might be a relevant empirical issue.

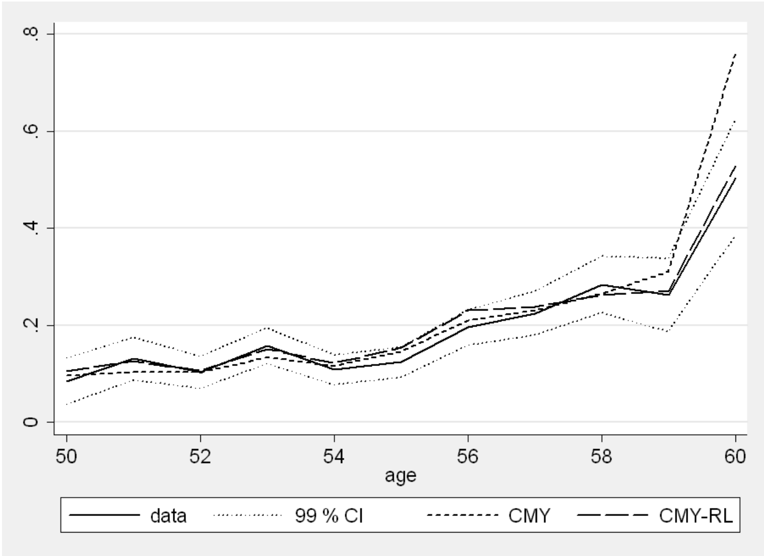
The results in Table 1 also show that there is considerable unobserved heterogeneity in the marginal value of leisure: the point estimate of the parameter σ_ζ is rather large (1.82, cf. column CMY-RL) and differs significantly from zero. However, according to the estimation results, only a small fraction (10.9 percent) of the population has a negative marginal value of leisure (i.e., $\kappa < 1$). For only 3.7 percent of the population, the marginal utility of retirement consumption is negative (i.e., $\kappa < 0$).

Comparing the MY-RL and CMY-RL estimates of κ_0, we again find evidence of dynamic self-selection: the estimate of the marginal value of leisure is biased downward in the MY-RL model.[24] It also turns out that the estimate of σ_ζ is smaller in the MY-RL model. This result can be explained by the phenomenon of dynamic self-selection: since individuals who love leisure have a higher tendency to retire prior to the base year, the MY-RL model underestimates the population variation in the marginal value of leisure.

The CMY-RL estimate for γ is found to be equal to 0.33; being significantly less than 1, this indicates that the utility function is a concave function of earnings. Although γ is rather low, it reveals a moderate degree of risk-aversion: according to this estimate, the certainty equivalent of the lottery €10,000 with probability 0.5 and €20,000 with identical probability is equal to €14,421. Few applications of the OV model to females are available in the literature. The most interesting one is Danø, Ejrnaes, and Husted (2005); by comparing our results with their results, it turns out that Italian female workers value leisure more than their Danish counterparts and are more risk-averse. It must be realized that this comparison is difficult, because Danø, Ejrnaes, and Husted (2005) analyzes non-married workers,

[24]Because of convergence problems, the parameter ρ is fixed to 0.661 in the MY-RL model (the estimate of ρ in the CMY-RL model).

Figure 3: Average hazard rates by age: females



whereas we analyze a whole population of female workers, and most of them are presumably married.

Figure 3 compares actual and predicted average hazard rates by age for females.[25] Overall, the CMY and CMY-RL models have excellent fit to the data. The two models are able to explain most of the humps at various ages. Predicted hazards are within the 99-percent confidence interval at every retirement age, except at age 60 for the CMY model. Cumulative retirement rates (not shown) provide a further confirmation of this result. For instance, at age 54 the actual cumulative rate is equal to 46.3 percent while the CMY-RL model predicts 47.9 (the CMY model forecasts 44.3).

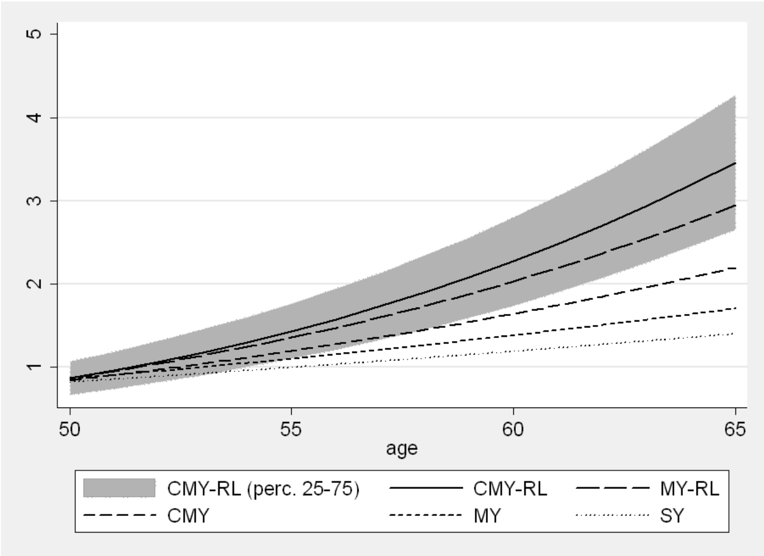
5.2 Males

Table 2 shows the estimation results for males. In all models (SY, MY, CMY, MY-RL and CMY-RL), the estimate of κ_1 is sizable and significantly

[25] In-sample fit and simulations for the random leisure models are based on posterior conditional distributions of ζ (see e.g. Train 2003). For the CMY-RL model, $\hat{\zeta}_i = (\int_{-\infty}^{\infty} \zeta/\sigma_\zeta \phi(\zeta/\sigma_\zeta) \mathscr{L}_i(.|\zeta) \mathrm{d}\zeta)/\mathscr{L}_i$ where $\mathscr{L}_i$ is given by equation (26) and $\mathscr{L}_i(.|\zeta) = (\int_{-\infty}^{B_{i\tau}} \dots \int_{-\infty}^{B_{it_0}} f(\xi_{t_0}, \dots, \xi_\tau|\zeta)\, \mathrm{d}\xi_{t_0} \dots \mathrm{d}\xi_\tau)/(\int_{-\infty}^{C_{it-1}} \dots \int_{-\infty}^{C_{it_0}} f(\xi_{t_0}, \dots, \xi_{t-1}|\zeta)\, \mathrm{d}\xi_{t_0} \dots \mathrm{d}\xi_{t-1})$. $\hat{\zeta}_i$ is approximated as $\left[\sum_{r=1}^{R} \zeta^r \mathscr{L}_i(.|\zeta^r)\right]/\mathscr{L}_i$, where ζ^r is a random draw from the empirical distribution of $(\kappa_0 + \zeta)$ and R=2500. Similar formulas are applied in the MY-RL model.

greater than zero. Figure 4 shows for all models the strong relationship between the marginal value of leisure (κ) and age.[26]

Figure 4: Estimated κ by age, males: different models



Notes: lines represent average values; the shadowed area includes the 25-75 percentiles of κ according to the CMY-RL model

In the SY model, we select workers aged 50 to 65 in year 1991. The sample size is much larger for males than for females (7,180 versus 1,341 workers). As for females, we assume that $\rho = 1$. Results for κ_0 and κ_1 suggest a negative value of leisure up to age 55 (See figure 4).

In the MY model, workers in the base year are followed for up to 11 years (see table 2), corresponding to 12 possible outcomes. In estimating this model, we therefore fully exploit the pension reforms of the 1990s. As in the case of females, the random walk assumption of the SY model is strongly rejected ($\rho = 0.11$, s.e. 0.03). The marginal value of leisure is higher than that found in the SY model at every retirement age, see figure 4. The MY estimate for κ is found to be significantly less than 1 only at ages 50 and 51.

As shown in figure 2, the correction for self-selection is incomplete for males since workers born in 1934 or earlier can be observed only after age 50. Consequently, the estimates of the CMY model for males must be interpreted

[26]Confidence intervals are not shown in figure 4 for ease of reading. Standard errors for κ are computed using the delta method. According to the CMY-RL model (median) these range from 0.03 at age 50 to 0.08 at age 65. The whole set of s.e. for the five models is available from the authors upon request.

Table 2: Option value parameter estimates: males

	Model				
	SY	MY	CMY†	MY-RL	CMY-RL†
Parameter					
κ_0	0.824	0.862	0.845	0.872	0.870
	(0.032)	(0.023)	(0.012)	(0.012)	(0.002)
κ_1	2.028	2.602	3.647	4.645	5.265
	(0.167)	(0.243)	(0.302)	(0.172)	(0.108)
γ	0.314	0.329	0.292	0.375	0.361
	(0.041)	(0.033)	(0.034)	(0.004)	(0.001)
ρ	1*	0.114	0.304	0.303*	0.303
	-	(0.028)	(0.024)	-	(0.029)
σ_ξ	0.961	7.366	4.921	7.885	7.721
	(0.123)	(2.858)	(1.874)	(0.215)	(1.183)
σ_ν		9.909	5.286	10.048	9.024
		(2.021)	(1.280)	(0.045)	(0.562)
σ_ζ				0.266	0.301
				(0.008)	(0.003)
Summary statistics					
N.Obs.	7180	32125	32125/54943	32125	32125/54943
N.Ind.	7180	7180	7180	7180	7180
$-\log \mathscr{L}$	2003.24	10916.36	10928.27	10862.14	10832.50
est.method	ML	SML	SML	SML,GHQ	SML,GHQ

Notes: † = only a partial correction for self-selection is possible; $\beta = 0.76$; * = value imposed; s.e. in parenthesis; monetary values are in €1,000 (2009 euros); ML is maximum likelihood, SML is simulated maximum likelihood (GHK simulator with 100 random draws plus antithetics), GHQ is Gauss-Hermite quadrature (10 points).

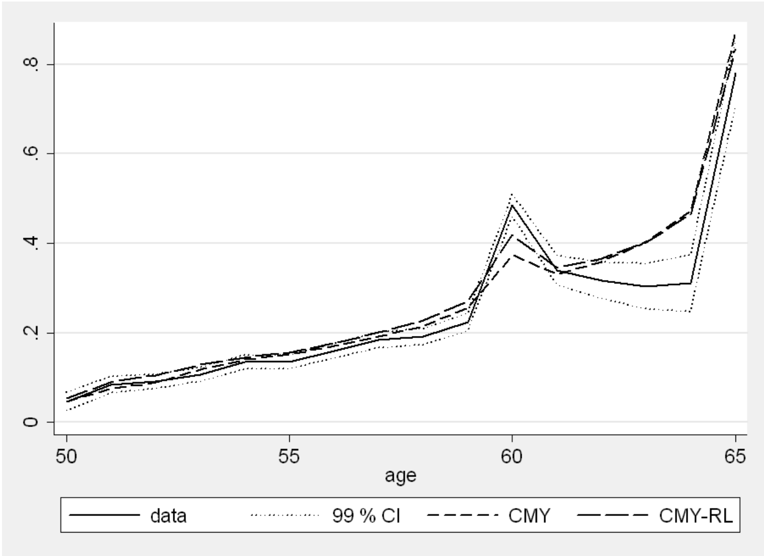
with caution. The comparison between MY and CMY results yields only a first (underestimated) quantification of the effect of self-selection. In the CMY model, κ is estimated to be, e.g., 1.19 at age 55, 1.64 at age 60, and 2.20 at age 65. The corresponding values for the MY model are 1.10, 1.39 and 1.71. The effect of dynamic self-selection on κ goes in the expected direction: the value of leisure is underestimated by the MY model. Note that by assuming functional form (24) for κ, the effect of self-selection bias (i.e., the difference between the estimated κ's in the MY and CMY models at the same age) is increasing with age. This conforms with the model: particularly older workers who are work-lovers are included in the sample; the sample is less selected at younger ages.

The results in Table 2 (cf. the column CMY-RL) also indicate that there is a lot of variation across individuals in the marginal value of leisure (see the large and significant point estimate of the parameter σ_ζ). Comparing the MY-RL and CMY-RL estimates of κ, we again find evidence that, due to dynamic self-selection, the estimate of the marginal value of leisure is biased downward in the MY-RL model.[27]. It is worthwhile to note that the point estimates of the age parameter κ_1 and of the risk aversion coefficient γ are considerably larger in the random coefficient versions of the CMY and MY models.

Figure 5 shows actual and predicted average hazard rates by age for males. Up to age 59, the CMY and CMY-RL models have a good fit. They only slightly overestimate transitions into retirement: the actual cumulative retirement rate at age 59 is equal to 77.2 percent, while the CMY-RL model predicts 81.9. At age 60, the data show a large spike in exit rates, equal to 48.5 percent. The CMY-RL model is able to capture this only in part, predicting a retirement rate equal to 41.8 percent. At this age, this model performs better than the CMY model, which predicts a lower hazard. Spikes in exit rates at typical retirement ages are a common finding in the retirement literature (see e.g. Gruber and Wise 2004a). Most models that quantify the impact on retirement of financial incentives either completely or partly fail to capture them (see applications in Gruber and Wise 2004b). An underestimation of spikes in exits is often explained by the existence of "customary age effects" (see e.g. Stock and Wise 1990). Finally, hazards at

[27] Because of convergence problems, the parameter ρ is fixed at 0.303 in the MY-RL model (the estimate of ρ in the CMY-RL model).

Figure 5: Average hazard rates by age: males



ages 62 and above are overestimated, but this is less relevant, since these apply to a small number of workers (the cumulative retirement rate at age 61 is equal to 93.1 percent).

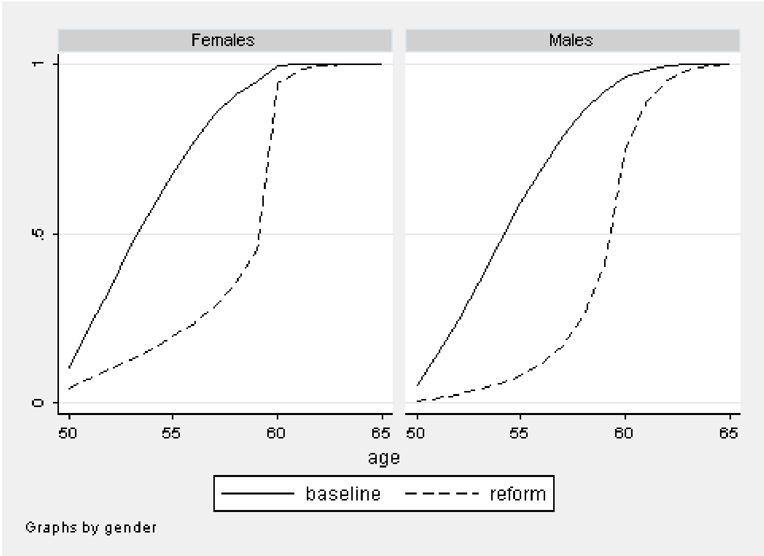
5.3 Evaluation of a hypothetical pension reform: a simulation

In this section, we exploit the estimated models to simulate the impact on retirement of a hypothetical pension reform. This reform is taken from Gruber and Wise (2004b).[28] The new system sets the early retirement age at 60 and the normal retirement age at 65. The replacement rate at age 65 is equal to 60 percent of earnings at age 60. Finally, the pension benefit is reduced by 6 percent for each retirement year before 65 and increased by the same percentage for each retirement year after age 65.

In comparison with the legislation actually implemented in the sample period, this reform would introduce a more actuarially fair pension formula: as already discussed in section 2, actual rules grant a return of 2 percent for each additional year of work, providing a strong incentive toward early retirement. Moreover, for most workers in the sample, this reform would increase the minimum age at which they become eligible for pension benefits.

[28]The same simulation is also run in Belloni and Alessie (2009).

Figure 6: Average cumulative retirement rates by age: CMY-RL



For the simulations, we construct a "simulation sample" in the same way as Brugiavini and Peracchi (2004). In the simulation sample, we consider the same workers present in the estimation sample, but we abstract from their actual retirement choices, i.e., we allow for all of them to continue working up to age 70. We use the estimated wage model (27-28) to predict workers' future wages after their actual retirement age. Using the simulation sample, we then predict workers' retirement probabilities under both the actual (baseline) and the hypothetical legislation.

The reform seems to have a strong impact on retirement choices: according to the CMY-RL model, female average retirement age increases by 1.97 years. Most of the effect can be imputed to tightened eligibility more than to introduction of an actuarially fair pension formula. At age 60 (the minimum retirement age under the reform), the simulated hazard rate in the hypothetical pension system is equal to 90 percent and the cumulative retirement rate is equal to 94 percent (see figure 6, left panel). For males, we find a somewhat weaker effect from the reform: average retirement age increases by 1.57 years. Male cumulative hazard rate at age 60 in the simulated reform is equal to 75 percent (see figure 6, right panel).

Importantly, if we use the estimated MY-RL model - instead of the CMY-RL model - to simulate the effect of the reform on female retirement, we find a stronger effect: average retirement age increases by 2.18 years (cf. with 1.97 years). Since the MY-RL model underestimates the value of leisure, it over-predicts females' reaction to changes in financial incentives. This simulation suggests that this bias is not negligible: +0.21 years, i.e., 11 percent of the average effect of the reform.[29]

6 Conclusions

Using Italian administrative data, this study estimates an OV model to quantify the effect of financial incentives on retirement choices. As far as we know, this is the first empirical analysis to estimate the CMY model put forward by Stock and Wise (1990). This implies that we account for dynamic self-selection bias. van Soest, Kapteyn, and Zissimopoloulos (2007) argue that the preference for leisure is affected by factors not observed by the econometrician. To account for this, we also estimate an extended version of the model in which the marginal value of leisure is random.

We find plausible estimates of the preference parameters, such as the marginal utility of leisure. From a comparison of the results obtained by the conditional versions of the model with those obtained by the models that do not correct for dynamic self-selection, it becomes clear that dynamic self-selection results in a seriously downward-biased estimate of the marginal utility of leisure. In the random leisure version of the model, it also results in an underestimation of the population variation of the marginal utility of leisure. We perform a simulation study to gauge the effects of dramatic pension reform (see subsection 5.3 for details). The result is that the underestimation of the marginal utility of leisure translates into a sizable (11 percent) over-prediction of the impact of the reform on retirement.

For the female sample, the model is able to predict almost perfectly the age-specific hazard rates. The estimates of the CMY and MY models strongly suggest that preference shocks are much less persistent than assumed in the SY model (where full persistency is assumed). For the male sample, we obtain plausible estimates and a good fit. The estimates for males should, however, be interpreted with caution since we are not able to fully correct for dynamic self-selection bias.

[29] Comparing models without RL yields similar results. The female average retirement age increases by 2.18 years according to the CMY model, and by 2.47 years according to the MY model. The overestimation induced by dynamic self-selection in this case is therefore equal to 0.28 years, i.e., 13 percent of the effect of the reform.

One of the key assumptions of the OV model is that it does not account for savings, so that at each retirement age consumption is equal to current income. Obviously, savings and retirement choices are interrelated. It would therefore be important to use Italian data to estimate a structural retirement model that takes savings behavior into account (see e.g. French 2005).

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